

Hospital Readmission Risk Prediction: AI Case Study Solution

1. Problem Scope (5 points)

Problem Definition: The hospital faces significant financial penalties under Medicare's Hospital Readmissions Reduction Program for excessive 30-day readmissions, while also wanting to improve patient outcomes and reduce healthcare costs. Currently, discharge decisions rely heavily on physician intuition and basic clinical indicators, leading to inconsistent risk assessment.

Objectives:

- **Primary:** Reduce 30-day readmission rates by 15% within 12 months of implementation
- **Secondary:** Identify high-risk patients 24-48 hours before discharge to enable targeted interventions
- **Tertiary:** Decrease average length of stay by optimizing discharge timing for low-risk patients

Key Stakeholders:

- **Clinical Team:** Physicians, nurses, and case managers who will use predictions for discharge planning
- **Hospital Administration:** CFO and quality directors concerned with financial penalties and performance metrics
- **Patients and Families:** Direct beneficiaries of improved care coordination and reduced readmissions
- **IT Department:** Responsible for system integration and data security
- **Compliance Officers:** Ensuring HIPAA and regulatory adherence

2. Data Strategy (10 points)

Data Sources

Electronic Health Records (EHRs):

- Patient demographics (age, gender, insurance type)
- Medical history and comorbidities (diabetes, heart failure, COPD)
- Current admission details (diagnosis codes, procedures, length of stay)
- Vital signs trends during hospitalization
- Laboratory results and medication lists

Administrative Data:

- Previous admission patterns and readmission history
- Emergency department visits in past 6 months

- Discharge disposition (home, skilled nursing, rehabilitation)
- Social determinants (zip code for socioeconomic indicators)

Two Critical Ethical Concerns

1. Algorithmic Bias Leading to Health Disparities The model could perpetuate existing healthcare inequities by systematically flagging certain demographic groups as higher risk, potentially leading to longer hospital stays or different treatment protocols for minority patients. Historical data may reflect past biases in clinical decision-making, causing the AI to learn and amplify these patterns.

2. Patient Autonomy and Informed Consent Patients may not be aware that AI algorithms are influencing their discharge decisions and care plans. There's an ethical obligation to inform patients when automated systems contribute to clinical decisions that affect their treatment, while also ensuring they understand how their data is being used for predictive modeling.

Preprocessing Pipeline

Data Cleaning Phase:

- Handle missing values using clinical domain knowledge (e.g., impute normal ranges for missing lab values)
- Remove duplicate records and resolve patient identity matching issues
- Standardize medical coding systems (ICD-10, CPT codes)

Feature Engineering Steps:

- **Temporal Features:** Create time-based variables like "days since last admission" and "number of ED visits in 90 days"
- **Clinical Severity Scores:** Calculate Charlson Comorbidity Index and APACHE scores
- **Medication Complexity:** Count unique medications and flag high-risk drug combinations
- **Social Risk Indicators:** Derive socioeconomic status proxies from zip code data
- **Trend Analysis:** Extract vital sign trends (improving vs. deteriorating) during admission

3. Model Development (10 points)

Model Selection and Justification

Selected Model: Gradient Boosting Machine (XGBoost)

Justification: XGBoost excels in healthcare prediction tasks because it handles mixed data types (categorical diagnosis codes, continuous lab values) effectively and provides feature importance rankings

that clinicians can interpret. Unlike black-box deep learning models, XGBoost offers explainability crucial for clinical acceptance. It also performs well with the typically imbalanced datasets in healthcare (more patients don't get readmitted than do) and can capture complex non-linear relationships between clinical variables.

Performance Evaluation (Hypothetical Results)

Confusion Matrix:

	Predicted		
	No Readmit	Readmit	
Actual No Readmit	850	50	(900 total)
Actual Readmit	25	75	(100 total)

Calculated Metrics:

- **Precision:** $75 / (75 + 50) = 0.60$ (60%)
- **Recall (Sensitivity):** $75 / (75 + 25) = 0.75$ (75%)
- **Specificity:** $850 / (850 + 50) = 0.94$ (94%)

Clinical Interpretation: The model correctly identifies 75% of patients who will be readmitted, while maintaining low false positive rates (only 6% of non-readmit patients flagged). The 60% precision means that when the model predicts readmission, it's correct 60% of the time, which is clinically actionable for targeted interventions.

4. Deployment (10 points)

Integration Steps

Phase 1: Infrastructure Setup

- Deploy model on hospital's secure cloud environment with real-time API endpoints
- Integrate with existing EHR system (Epic, Cerner) through HL7 FHIR standards
- Create automated data pipelines to feed patient information to the model every 6 hours

Phase 2: Clinical Workflow Integration

- Embed risk scores directly into physician dashboards and discharge planning screens
- Design alert systems that notify case managers when patients cross high-risk thresholds
- Implement batch processing for daily risk assessments of all admitted patients

Phase 3: User Training and Rollout

- Train clinical staff on interpreting risk scores and recommended interventions
- Establish feedback loops for model performance monitoring and continuous improvement
- Create escalation protocols for high-risk patients identified by the system

HIPAA Compliance Strategy

Technical Safeguards:

- Implement end-to-end encryption for all data transmission and storage
- Use role-based access controls ensuring only authorized personnel can access patient predictions
- Deploy audit logging to track every access to patient risk scores and model predictions
- Conduct regular penetration testing and vulnerability assessments

Administrative Safeguards:

- Execute Business Associate Agreements (BAAs) with any third-party vendors involved in model hosting
- Establish data retention policies that automatically purge patient data after required timeframes
- Create incident response procedures specifically for AI-related data breaches
- Implement regular HIPAA compliance training focused on AI system usage

Physical Safeguards:

- Deploy models on HIPAA-compliant cloud infrastructure with appropriate certifications
- Ensure all workstations displaying patient risk scores have automatic screen locks and encryption

5. Optimization (5 points)

Regularization Through Cross-Validation and Feature Selection

Method: Recursive Feature Elimination with Cross-Validation (RFECV)

To address overfitting, I propose implementing RFECV combined with L1 regularization (Lasso). This approach systematically removes less important features while using 5-fold cross-validation to ensure the model generalizes well to unseen patient data.

Implementation Details:

- Start with all engineered features and iteratively remove the least important ones
- Use cross-validation scores (specifically, area under ROC curve) to determine optimal feature count
- Apply L1 regularization penalty to further constrain model complexity

- Monitor training vs. validation performance gaps to detect overfitting early

Clinical Benefits: This method not only prevents overfitting but also creates a more interpretable model with fewer features, making it easier for clinicians to understand which factors most strongly predict readmission risk. A simpler model with 15-20 key features is more trustworthy and actionable than a complex model with hundreds of variables.